IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 24 August 2022, accepted 8 September 2022, date of publication 19 September 2022, date of current version 22 January 2025.
Digital Object Identifier 10.1109/ACCESS.2022.3207751

RESEARCH ARTICLE

Blinder Oaxaca and Wilk Neutrosophic Fuzzy Set-Based IoT Sensor Communication for Remote Healthcare Analysis

OSAMAH IBRAHIM KHALAF[1], RAJESH NATARAJAN[2], NATESH MAHADEV[3], PRASANNA RANJITH CHRISTODOSS[2], THANGARASU NAINAN[4], CARLOS ANDRÉS TAVERA ROMERO[5], (Member, IEEE), AND GHAIDA MUTTASHAR ABDULSAHIB[6]
[1]Al-Nahrain Nanorenewable Energy Research Center, Al-Nahrain University, Baghdad 64074, Iraq
[2]Information Technology Department, University of Technology and Applied Sciences-Shinas, Shinas 324, Oman
[3]Department of Computer Science and Engineering, Vidyavardhaka College of Engineering, Mysuru, Karnataka 570002, India
[4]Department of Computer Science, Karpagam Academy of Higher Education, Coimbatore 641021, India
[5]Universidad Santiago de Cali, Santiago de Cali 760036, Colombia
[6]Department of Computer Engineering, University of Technology, Baghdad 10066, Iraq

Corresponding author: Rajesh Natarajan (rajesh.natarajan@shct.edu.om)

This work was supported by the Research General Direction at Universidad Santiago de Cali under Grant 01-2022.

ABSTRACT In the remote healthcare industry data analytics denotes the computerization of collection, processing, and exploring complicated data to acquire finer perceptions and validate healthcare practitioners to produce familiar decisions. Healthcare basics in the modern age are vital challenges specifically in developing countries owing to the shortfall of difficult hospitals and medical professionals. As fuzzy systems have reformed several areas of work, health has also made the most of it. In this paper, the purpose of the study is to introduce a novel and intelligent remote healthcare system based on modern technologies like the Internet of things (IoT) and Neutrosophic fuzzy systems to ensure precise data analysis with lesser time and energy consumption. In this study, a novel method called, Blinder Oaxaca-based Shapiro Wilk Neutrosophic Fuzzy (BO-SWNF) data analytics for remote healthcare is designed. Data collection is performed with the WESAD dataset. Duplicated data are eliminated by Blinder Oaxaca Linear Regression-based Preprocessing model. With the application of the Blinder Oaxaca function, energy efficiency is enhanced. Finally, the Shapiro Wilk Neutrosophic Fuzzy algorithm is applied for ensuring robust data analysis. The experimental results of the proposed BO-SWNF envisage the data for finer comprehension of attribute distribution. The result is conducted by using PYTHON application to analyze stress detection with the WESAD dataset. The proposed BO-SWNF method achieved an overall accurate data analysis of 12 % with minimum time ensuring 56 % improvement and minimizing energy consumption by 54 %.

INDEX TERMS Blinder Oaxaca, energy efficiency, IoT, linear regression, neutrosophic fuzzy, Shapiro Wilk.

I. INTRODUCTION

Several statistical methods have been playing a key role in data analytics, disease forecasting, and performing remote healthcare systems as far as medical sciences are concerned. In these fields, the research person and also practitioner's main role depends on the efficient screening of remote healthcare data for significant forecasting. Specifically, remote healthcare data measurements involved in screening and forecasting are not precise and are found to be fuzzy or in interval forms. As a result, neutrosophic logic was instigated as one of the universal formations of fuzzy logic for estimating truthiness, falseness, and indeterminacy for remote healthcare data analysis. Neutrosophic Multiple-Criteria Decision-Making

The associate editor coordinating the review of this manuscript and approving it for publication was Chan Hwang See.

(Neutrosophic MCDM) was proposed by Hezam *et al.* [1] to develop an exploratory perception for classifying and ranking the most exemplary groups for instigating priority in gaining vaccines even at the initial stage. Initially, data analysis was performed using Analytic Hierarchy Processing under uncertainty to estimate and rank main and sub-criteria, owing to the reason that the inputs were obtained in the form of neutrophilic numbers. Second, neutrosophic TOPSIS was also applied for ranking vaccine alternatives. Finally, using Analytic Hierarchy Processing ranking efficiency and classification accuracy were found to be improved via measuring the weights of the sub-criteria. Despite improvement observed in terms of classification accuracy, the energy consumed in the process of decision-making was not focused. To address this aspect, a Blinder Oaxaca Linear Regression-based Preprocessing model is designed. The advantage of using this Linear Regression-based Preprocessing with Blinder Oaxaca function dynamically adjusts the sensing frequency of each corresponding device to fit with dynamic changes along with the monitored vital sign. This in turn reduces energy consumption.

Grubbs's test under Neutrosophic Statistic (Grubb's test under NS) was designed by Aslam [2] for medical data analysis. The method was found to be a generalization of Grubbs's test under traditional statistics. Also, the designing and operational structure employing the neutrosophic statistical interval method was modeled using real data from the medical field. With this statistical interval method outliers in data were identified in a significant manner.

Despite the minimization of outliers observed in Grubb's test under NS, both paramount performance factors like, accuracy and time involved were not concentrated. To focus on this topic, the Shapiro Wilk Neutrosophic Fuzzy algorithm is applied. With this algorithm, the decision-making test is performed using the Shapiro Wilk function. With this function, not only outliers are eliminated during decision making but also assist in enhancing overall data analysis accuracy and time to a greater extent.

With the development of IoT ushers the users with novel chances in several applications, to name a few being smart cities and smart healthcare. Presently, the preliminary utilization of IoT in healthcare can be classified into two types remote monitoring and real-time health systems. Controlling and managing the data, related to COVID-19 laid the mechanism for remote monitoring was analyzed with the aid of IoT systems.

An endeavor was made by Antonysamy *et al.* [3] where neutrosophic sets were applied to medical data. By utilization of advanced Hausdorff minimum distance core symptoms of the patient were obtained wisely. Also, with decision implementation using minimum distance estimation, a clue for the type of disease influencing the patient in addition to core symptoms was obtained, therefore improving accuracy. However, the time factor was not focused.

With the aid of IoT health monitoring systems and systematic data analysis, frequent visits to doctors can be avoided between patients and medical professionals. However, several patients necessitate intermittent health monitoring at regular time intervals. To address this concern, Bhardwaj *et al.* [4] designed a smart health monitoring system was designed employing IoT technology that with the blood pressure, heart rate, oxygen level, and temperature data provided by the patient was found to be very useful in making early decision making. With efficient decision-making, however, the time factor involved in overall decision-making was not focused.

With the aid of digital data collection in the process, an enormous amount of data has to be analyzed every second. Also, with the increase in electronic record keeping, applications, and several other data collections using electronic means and storage, there is a paramount necessity for data to be obtained in real-time.

Vedaei *et al.* [5] proposed a prospective application of the IoT in remote healthcare for pandemic situations The proposed method was split into three sections, a lightweight IoT node, an application involving a smartphone, and finally fog-based Machine Learning tools for data analysis. With these three sections, the energy usage and bandwidth were found to be low. However, the accuracy remaining the major factor of analysis was not focused on, therefore compromising the overall accuracy.

As far as the coronavirus disease is concerned, the complexity involved was the Multi-Criteria Decision Making that in turn necessitated solid and robust means for data analysis. To enhance the accuracy, Alsalema *et al.* [6] proposed a data analysis model employing T Spherical Fuzzy sets (T-SFSs) for handling uncertainty in the data and obtaining information. The methodology was designed based on the decision matrix adoption and development phases. With this, the prioritization results were found to be supported with high correlation, therefore improving the accuracy aspect, but compromising the time factor.

In this research, the methods to improve energy consumption, the proposed method uses data analytics models for preprocessing and actual data analysis. Linear Regression-based Preprocessing with Blinder Oaxaca function is used to perform preprocessing for eradicating the duplicated data. The actual energy consumed is said to be reduced. Also, to improve accuracy and time, Shapiro Wilk Neutrosophic Fuzzy function is utilized using Shapiro Wilk function to improve both accuracy and time factor. A set of simulations on healthcare data is conducted in order to show the efficiency of our method while comparing the results to other existing methods.

A. CONTRIBUTIONS OF THE WORK

The contributions of the work include the following:

- This work addresses ensuring accurate data analysis with minimum time and energy consumption, through a BO-SWNF for remote healthcare data analysis by combining a novel preprocessing and data analysis model.
- This paper utilizes a novel Blinder Oaxaca Linear Regression-based Preprocessing model for eradicating

duplicate data to reduce the IoT sensor energy consumption during data sensing from two different devices.
- This paper employs a novel Shapiro Wilk Neutrosophic Fuzzy Data analysis to ensure robust and accurate decision-making based on analyzed data. Therefore, smooth communication between patients and medical practitioners is ensured.
- The proposed BO-SWNF method against Neutrosophic MCDM and Grubb's test under NS methods is implemented and comparative data analysis performances are performed. BO-SWNF method is proven to be practical and IoT sensor communication for remote healthcare analysis.

B. ORGANIZATION OF THE PAPER

The remainder of this paper is organized as follows. Section 2 presents an overview of several data analytics techniques related to associated remote healthcare existing in the literature. In Section 3, the three phases proposed in our method are detailed. Section 4 explains the obtained results and discusses them in detail. Section 4 provides the experimental result of the proposed method BO-SWNF and an evaluation of other data analytics methods. Also, a comparison between different measurement performances is provided. Finally, Section 5 concludes the paper.

II. RELATED WORKS

Over the past few years, different data analysis has found a good place to enhance remote healthcare systems. It has not only improved everyday operations but also assisted in patient care. Therefore, predictive modeling is used to examine the patterns for providing the set of input data. The modeling aims to examine current and historical data for forecasting future results. Thus, owing to this reason, efficient data analysis is used not only for historical information but also to employ datasets in tracking recent trends and making a decision.

A potential prevention mechanism was designed by Razzaq *et al.* [7] for assisting the decision makers in making significant decisions according to public acceptance and interposition efficiency. Here, linguistic terms were measured by employing triangular fuzzy numbers and Group Multi-Criteria Decision Making (GMCDM) technique. With this technique, the time involved in decision-making was found to be reduced.

To ensure security, the fuzzy and block-based adaptive model was designed by Zulkifl *et al.* [8]. Several uncertainties are still said to persist during the investment period and while acquiring the data for assessment. For such a lack of data, interval type-2 fuzzy logic is said to fit like a glove for vague conditions. Tolga [9] performed an interval type-2 fuzzy set integrated real option data analysis for device evaluation concerning medical treatment. However, with ambiguous information, accuracy and accurate decision-making were not ensured. To focus on this topic, yet another neutrosophic multi-criteria decision-making model was designed by Abdel-Basset *et al.* [10]. With this not only the mortality rate came down but also the cost was cut to a greater extent related to heart failure. However, the time factor involved in decision-making was not again concentrated.

To consider the time factor in decision making, Pamucar *et al* [11] discussed a novel fuzzy neutrosophic-based method. The data from the supplier was employed in designing, implementing, and finally performing a detailed analysis of multi-attribute evaluation concerning fuzzy neutrosophic values. Also, by employing pair-wise comparison, the significance of weight was determined for dealing with fuzzy neutrosophic sets. Therefore sensitivity is higher with accuracy. Yet another data analysis method employing an analytic hierarchy process was designed Bilandi *et al.* [12] with the objective of reducing energy consumption while selecting relay nodes for data transmission. However, both methods lacked the time involved along with the focus on accuracy.

To overcome the concern, A modified salp swarm optimization was designed by Khan and Algarni [13] and was integrated with an adaptive neuro-fuzzy inference system. The data was acquired using the Levy flight algorithm for heart disease diagnosis. Despite disease diagnosis accuracy along with the precise results, the time involved in detection was not addressed.

A dynamic model for data analysis using Heuristic Hybrid Time Slot Fuzzy-Allocation Algorithm (HHTSF-AA) was proposed by Kumar and Dhulipala [14] to enhance health monitoring by using IoT assisted wearable sensor platform. With this, both channel utilization and time were found to be improved on IoT-assisted wearable sensor platforms. Though the time factor was focused, the accuracy with which the health monitoring was not focused. Gulistan and Khan [15] applied a neutrosophic fuzzy set via a complex fuzzification model for enhancing both the accuracy and precision part. Despite improvement being observed in accuracy and precision, the computational time was not focused.

Yet another method for smart data analysis was presented by Islam *et al.* [16] by employing a smart healthcare monitoring framework. On one hand, techniques like IoT and Cloud frameworks were accurately obtainable. On the other hand, a substantial requirement to instigate an intuitive instrument for medical intended requirements to safeguard one's life is also said to be essential. But, the patient's condition was not considered.

To address this patient's condition, the work proposed by Zouka and Hosni [17] integrated artificial intelligence technology, like neural networks and fuzzy systems in a secure healthcare monitoring framework to ensure the overall system in performing a smart healthcare model. This type of model regulated priority based on the health data and vital signs collected from senor nodes. With this both the accuracy and reliability were said to be ensured. Despite accuracy and reliability, precision and time factors were not said to be focused.

To focus on the time factors, Kondaka *et al.* [18] introduced a bridge between the two by employing a novel algorithm called, iCloud Assisted Intensive Deep Learning (iCAIDL). This integrated framework ensured not only assistance to healthcare medium but also patients via an intelligent cloud system along with machine learning techniques from deep learning principles, therefore improving the data transfer ratio. Yet another data communication and transmission model was designed using deep learning algorithms by Wu *et al.* [19] for real-time health monitoring. With the aid of deep learning algorithms, precision and time were said to be improved.

Clarifying data collection and organization for remote healthcare is an encouraging step for most healthcare organizations. However, a lack of tools for collecting the most pertinent data remains a major portion of the area to be addressed. Hence, healthcare data analytics assists organizations exhibit vital information in identifying opportunities to ensure accuracy at an inexpensive cost.

Hudson [20] designed a systematic review to synthesize and analyze Internet of Medical Things-driven remote monitoring for COVID-19. Stone *et al.* [21] analyzed several research works applying machine learning techniques in COVID-19 detection and monitoring investigated in detail. Also, an in-depth analysis of the contribution to COVID-19 diagnosis, monitoring the trends, and remotely providing treatment using biosensors, and Internet of Medical Things devices was provided for tracking the same. Moreover, the clinical support system in case of persons detected with COVID-19 via smart healthcare devices was designed by Blazek *et al.* [22].

Motivated by the above materials and methods, in this work, a novel IoT sensor communication method for remote healthcare data analysis called, Blinder Oaxaca-based Shapiro Wilk Neutrosophic Fuzzy (BO-SWNF) is proposed. An elaborate description of the BO-SWNF method is provided in the following sections.

III. THE PROPOSED BLINDER OAXACA-BASED SHAPIRO WILK NEUTROSOPHIC FUZZY (BO-SWNF) FOR REMOTE HEALTHCARE DATA ANALYSIS

The BO-SWNF is a proposed method combining the linear regression concepts represented by the Blinder Oaxaca function and indeterminacy concepts of the Neutrosophic Fuzzy set to handle robustness and accuracy for remote healthcare data analytics. Figure 1 shows the block diagram of the BO-SWNF method for remote healthcare data analysis.

As shown in the below figure, first, data collection is performed using the WESAD dataset. Second, with the collected data, duplicate records are eliminated via normalization using the Blinder Oaxaca Linear Regression-based Preprocessing model. Finally, with the processed medical healthcare data, robust and accurate data analysis is made by employing the Shapiro Wilk Neutrosophic Fuzzy Data analysis model. To estimate performance metrics, the BO-SWNF method is used by providing better outcomes. As a result, with healthy decision-making, smooth communications between patients and medical practitioners are said to be ensured. An elaborate description of the proposed BO-SWNF method is given in the following sections.

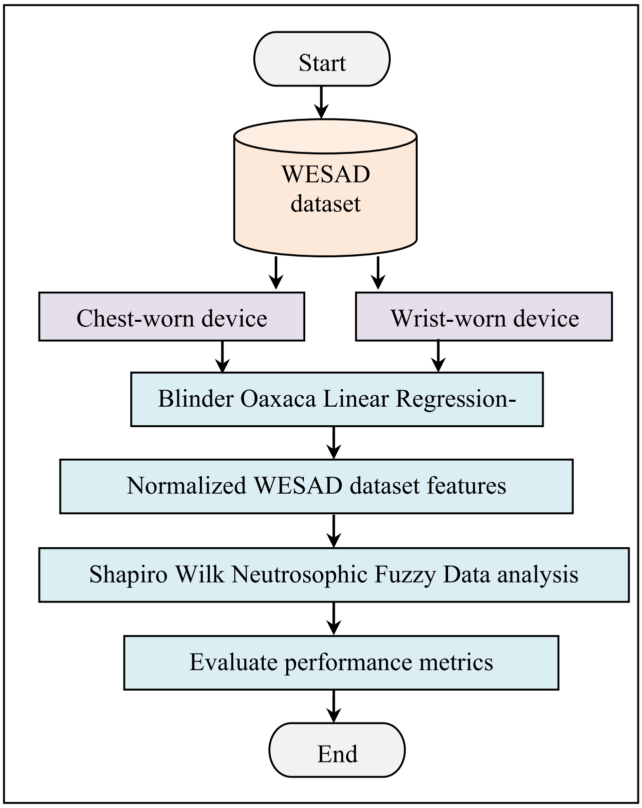

FIGURE 1. Flowchart of the proposed BO-SWNF method steps for analyzing the WESAD dataset.

TABLE 1. Wesad dataset description.

1	SX_readme.txt	consists of the information about the subject 'SX' and information pertaining to the collected data and quality respectively.
2	SX_quest.csv	consists of all relevant information
3	SX_respiban.txt	consists of data obtained from the RespiBAN device
4	SX_E4_Data.zip	consists of the data from the Empatica E4 device

A. DATA COLLECTION

In our work for performing Remote Healthcare Data Analytics, the data has to be acquired. The data for the processing of the proposed method are acquired from WESAD (Wearable Stress and Affect Detection) dataset. The dataset is organized in such a manner that each subject has a folder 'SX', where X denotes the subject ID. Moreover, each subject folder comprises the following files as given in table 1.

Moreover, the raw sensor data for processing the proposed method are recorded with the aid of two devices, a chest-worn device (RespiBAN) and a wrist-worn device (Empatica E4). The signals obtained from RespiBAN were sampled at 700 Hz. The SX_respiban.txt contains the raw data where

TABLE 2. Lists the data obtained from respiban.

1	SID	Sequential line number
2	---	Ignored
3	ECG (mV)	Electro Cardio Gram
4	EDA (μS)	Electro Dermal Activity
5	EMG (mV)	Electro Myo Gram
6	Temp ($°C$)	Body Temperature
7	X (g)	X – Channel accelerated data
8	Y (g)	Y – Channel accelerated data
9	Z (g)	Z – Channel accelerated data
10	Respiration (%)	Respiration

TABLE 3. Data from empatica.

1	ACC.csv	Three axis acceleration
2	BVP.csv	Blood Volume Pulse
3	EDA.csv	Electro Dermal Activity
4	TEMP.csv	Body Temperature

10 columns are present. The first column represents the sequential line number, the second column is ignored, and columns 3 – 10 contain the raw data of the 8 sensor channels with the channel orders defined in the header. Moreover, the entries "XYZ" refer to the 3-channel accelerometer and hence the acceleration data is provided in 3 columns separately. Table 2 given below lists the data obtained from RespiBAN.

Finally, the Empatica E4 device was worn on the subjects' non-dominant wrist. Here, the sampling rate of different sensors was distinct. Table 3 given below lists the details obtained from Empatica E4 device.

With the above details and the dataset structure 15 subjects were included during a lab study with the following sensor modalities included, namely, blood volume pulse, electrocardiogram, electro dermal activity, electro myogram, respiration, body temperature, and three axes acceleration respectively.

B. BLINDER OAXACA LINEAR REGRESSION-BASED PREPROCESSING MODEL

Data cleaning or preprocessing is one of the essential steps for remote healthcare analysis. This is owing to the reason that data cleaning comprises eliminating incorrect data and checking for inconsistencies. Also, not all of the data are found to be useful, hence cleaning at this stage is inevitable. During the data cleaning stage, duplicate records and basic errors are eliminated. Hence, data cleaning becomes mandatory before the sending of information for further analysis. In our work, Blinder Oaxaca Linear Regression-based Preprocessing model is designed. Here, with the aid of the Blinder Oaxaca Linear Regression function normalization is performed to eliminate duplicate data. Figure 2 shows the block diagram of the Blinder Oaxaca Linear Regression-based Preprocessing model. As shown in the below figure, the data cleaning process for remote healthcare data analytics is performed via IoT sensors that are placed on the patient body

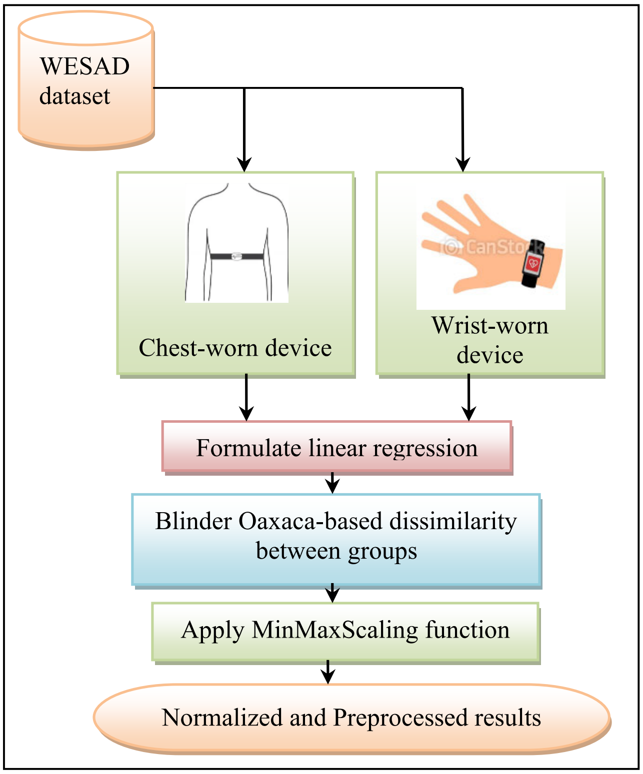

FIGURE 2. Block diagram of blinder oaxaca linear regression based preprocessing model.

for obtaining vital signs ('V=V_1, V_2,…,V_m' as given in table 1, 2 and 3).

Let us assume that we have a set of patients '$P = (P_1, P_2, \ldots, P_n)$' where each patient is assigned with distinct types of devices (i.e., RespiBan 'R' and Empatica 'E') to acquire the vital signs of the patient. For analysis purposes, let us further assume that each device '$\left(R_v^P, E_v^P\right)$' allocated to the patient 'P_i' monitors periodically vital signs '$v \in V$' for preprocessing. Thus, each '$\left(R_v^P, E_v^P\right)$' collects a vector '$\left(RV_v^P[t], EV_v^P[t]\right)$' of '$\tau$' records during a period of time 't' given as '$\left(RV_v^P[t], EV_v^P[t]\right) = [a_1, a_2, \ldots, a_\tau], [b_1, b_2, \ldots, b_\tau]$'. As not all the vital signs obtained from the patients are utilized for further processing, initially, a linear regression function is formulated separately for two devices. Then, at sequence, the Blinder Oaxaca Linear Regression-based Preprocessing algorithm produces record vectors of the first 'α' periods based on Linear Regression as given below.

$$RV = R_v^P[1], \quad R_v^P[2], \ldots\ldots, R_v^P[t] \tag{1}$$
$$EV = E_v^P[1], \quad E_v^P[2], \ldots\ldots, E_v^P[t] \tag{2}$$

Equations (1) and (2) are based on Linear Regression, for each device (RespiBan 'R' and Empatica 'E'), 'RV' and 'EV' acts as the training data. Then, the linear regression model separately for two devices is formulated as given below with an error variable 'ε_i' (i.e., 0.01) and 'ε_j' (i.e., 0.02) that add up the noise to the linear relationship between vital signs 'v'

and patients 'P_i' for an intercept 'α, β' respectively.

$$y_i = \alpha R_v^{P1}[1] + \alpha R_v^{P1}[2] + \ldots + \alpha R_v^{Pm}[t] + \varepsilon_i \quad (3)$$
$$y_j = \beta R_v^{P1}[1] + \beta R_v^{P2}[2] + \ldots + \beta R_v^{Pn}[t] + \varepsilon_j \quad (4)$$

With the resultant values of the above (3) and (4), though a huge amount of vital signs of patients are collected, results in swift depletion of accessible energy of sensors and also mess up with the overall data analysis process. Hence, to address this concern, Kitagawa Blinder Oaxaca decomposition is utilized in our work. The Kitagawa Blinder Oaxaca decomposition elucidates dissimilarities in the means between two groups (i.e., from two devices). The basic idea of this function is to dynamically adapt the sensing frequency of each device to fit with arbitrary dissimilarities of the monitored vital sign. In this way, energy efficiency can be improved to a greater extent. The function is mathematically stated as given below.

$$REV = RV\left[\mathrm{Mean}(y_i) - \mathrm{Mean}\left(y_j\right)\right] + \mathrm{Mean}\left(y_j\right)(RV - EV) \quad (5)$$

With the above linear regressive decomposition of two distinct vectors from (5), normalization is performed to scale up data with different types by employing the MinMaxScaling function.

$$NV[RV]_i^n = \frac{NV_i[REV] - MIN\left[RV_i^P(t)\right]}{MAX\left[RV_i^P(t)\right] - MIN\left[RV_i^P(t)\right]} \quad (6)$$
$$NV[EV]_i^n = \frac{NV_i[REV] - MIN\left[EV_i^P(t)\right]}{MAX\left[EV_i^P(t)\right] - MIN\left[EV_i^P(t)\right]} \quad (7)$$
$$R = PRD = \left\{NV[RV]_i^n, NV[EV]_i^n\right\} \quad (8)$$

where (6), (7) and (8), the normalized data from the devices 'RespiBan' and 'Empatica' as a preprocessing step is generated based on the normalized values '$NV_i[REV]$', minimum and maximum records '$MIN\left[RV_i^P(t)\, MIN\left[EV_i^P(t)\right]\right],$', $MAX\left[RV_i^P(t)\right], MAX\left[EV_i^P(t)\right]$' before performing data analytic process towards prediction. The pseudo-code representation of Blinder Oaxaca Linear Regression-based Preprocessing is given below.

As given in the below Blinder Oaxaca Linear Regression-based Preprocessing algorithm, the objective remains in normalizing raw healthcare data for further data analytics. With this objective, with the WESAD dataset obtained as input, two distinct vectors are generated to acquire different data from two different devices (i.e., the overall overhead as all the vital signs are not maintained in a single vector but different vectors) with numerous vital signs (i.e., from sensors). Next, data normalization is performed by means of Blinder Oaxaca function wherein MinMax Scaling has applied separately two different devices with numerous vital signs, therefore, obtaining the preprocessed data in a computationally efficient manner.

Algorithm 1 Blinder Oaxaca Linear Regression-Based Preprocessing

Input: Dataset 'DS', vital signs ('$V = V_1, V_2, \ldots, V_m$'), patients '$P = (P_1, P_2, \ldots, P_n)$'

Output: computationally efficient preprocessing 'R'

1: **Initialize** 'm', 'n', time 't', records 'τ', error variable 'ε_i' and 'ε_j'
2: **Initialize** devices RespiBan 'R' and Empatica 'E'
3: **Begin**
4: **For** each Dataset 'DS' from patients 'P' recorded with vital signs 'V'
5: Formulate RespiBan vector as in equation (1)
6: Formulate Empatica vector as in equation (2)
7: **For** each vital signs 'v' and the patients 'P_i'
8: Formulate linear relationships as in equations (3) and (4)
9: Formulate the dissimilarities in the means between two groups as in equation (5)
10: Estimate MinMaxScaling for RespiBan vector and Empatica vector as in equations (6) and (7)
11: **Return** preprocessed resultant data (R)
12: **End for**
13: **End for**
14: **End**

C. SHAPIRO WILK NEUTROSOPHIC FUZZY DATA ANALYSIS

Upon successful completion of preprocessing, relevant and meaningful data have to be extracted. Here, hidden patterns and relationships have to be derived to identify depth insights and predictions for arriving at conclusions. This is owing to the reason utilization of health data analytics permits improvements to patient care, accurate diagnoses, and more informed decision-making in a timely manner. In this section, with this objective a novel model called, Shapiro Wilk Neutrosophic Fuzzy sets are designed for remote healthcare data analysis. Figure 3 shows the block diagram of the Shapiro Wilk Neutrosophic Fuzzy Data analysis model.

As illustrated in the below figure, with the processed remote healthcare data obtained from the WESAD dataset, initially, a fuzzy set formulation is performed by means of a neutrosophic function. Followed by which two distinct operations, namely union and intersection are subjected for the fuzzified results. Finally, a test of normality is applied to the union and intersection-operated results via the Shapiro Wilk function, therefore extracting robust remote healthcare data analysis. Let 'R' be a set of objects (i.e., a set of preprocessed resultant data) and '$Q = \left\{\left(r, \mu_Q(r)\right), \mu_Q(r) \in [0,1], r \in R\right\}$' represent a fuzzy set. Then, Shapiro Wilk Neutrosophic Fuzzy Data analysis 'Q' in 'R' is defined as given below.

$$Q = \left\{r, \mu_Q(r), T_Q(r,\mu), I_Q(r,\mu), F_Q(r,\mu)\right\}, \text{ where } r \in R \quad (9)$$

Here. the neuro membership value is expressed in three different forms, i.e., true value '$T_Q(r,\mu)$', indeterminacy value '$I_Q(r,\mu)$' and false value '$F_Q(r,\mu)$' respectively. Let '$R = \{r_1, r_2, \ldots, r_n\}$, wheren $= 10 + 4 = 14$',

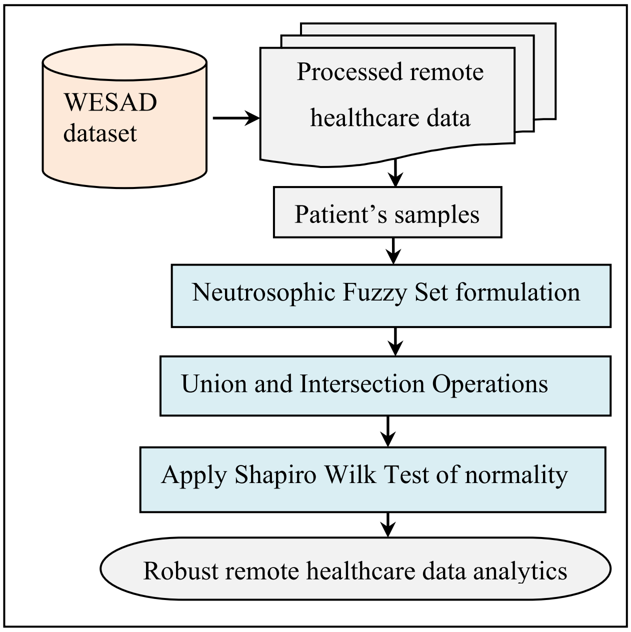

FIGURE 3. Block diagram of shapiro wilk neutrosophic fuzzy data analysis model.

(i.e., 10 features from RespiBan vector and 4 features from Empatica vector respectively) and 'P_i' and 'P_j' be two patients which are expressed using Shapiro Wilk Neutrosophic Fuzzy Data analysis of 'R', then 'P_i' and 'P_j' are defined as given below.

$$P_i = \begin{pmatrix} r_1 & r_{11} & r_{12} & r_{13} & r_{14} \\ r_2 & r_{21} & r_{22} & r_{23} & r_{14} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ r_n & r_{n1} & r_{n2} & r_{n3} & r_{n4} \end{pmatrix};$$
$$P_j = \begin{pmatrix} r_1 & r_{11} & r_{12} & r_{13} & r_{14} \\ r_2 & r_{21} & r_{22} & r_{23} & r_{14} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ r_n & r_{n1} & r_{n2} & r_{n3} & r_{n4} \end{pmatrix}; \quad (10)$$

From (10), two patients 'P_i' and 'P_j' 14 factors of medical analysis with '$n = 14$'are expressed, for factor 'r_1' using Shapiro Wilk Neutrosophic Fuzzy Data analysis where 'r_{11}' represents the fuzzy membership value, 'r_{12}' represents the true membership value, 'r_{13}' and 'r_{14}' denotes the indeterminacy and false membership value respectively. Then, with the above representations, two distinct operations, i.e., union and intersection are performed as given below.

$$P_i \cup P_j = \left\{ \begin{matrix} \mathrm{MAX}\left[\mu_{P_i}(r), \mu_{P_j}(r)\right], \mathrm{MAX}\left[T_{P_i}(r), T_{P_j}(r)\right], \\ \mathrm{MAX}\left[I_{P_i}(r), I_{P_j}(r)\right], \mathrm{MAX}\left[F_{P_i}(r), F_{P_j}(r)\right] \end{matrix} \right\} \quad (11)$$

$$P_i \cap P_j = \left\{ \begin{matrix} \mathrm{MIN}\left[\mu_{P_i}(r), \mu_{P_j}(r)\right], \mathrm{MIN}\left[T_{P_i}(r), T_{P_j}(r)\right], \\ \mathrm{MIN}\left[I_{P_i}(r), I_{P_j}(r)\right], \mathrm{MIN}\left[F_{P_i}(r), F_{P_j}(r)\right] \end{matrix} \right\} \quad (12)$$

Finally, to perform data analysis, with choices and standards as a basis, the Shapiro–Wilk test is a test of normality performed to improve the benefit (i.e., data analysis accuracy) and reduce the cost (i.e., data analysis processing time) is modeled. Let '$C = \{c_1, c_2, \ldots, c_m\}$' be the set of choices and '$S = \{s_1, s_2, \ldots, s_n\}$' be the set of standards. The features of choices 'c_i, where $i = 1, 2, \ldots m$' corresponding to the standards 's_j, where $j = 1, 2, \ldots, n$' is denoted as given below.

$$\begin{aligned} c_i &= \left\{s_j, \mu_{c_i}(s_j), T(s_j, \mu_{c_i}), I(s_j, \mu_{c_i}), F(s_j, \mu_{c_i})\right\} \\ &\quad T(s_j, \mu_{c_i}), \quad I(s_j, \mu_{c_i}), \; F(s_j, \mu_{c_i}) \in [0, 1] \\ 0 &\le T(s_j, \mu_{c_i}), \quad I(s_j, \mu_{c_i}), \; F(s_j, \mu_{c_i}) \le 3 \end{aligned} \quad (13)$$

This article has considered the perception of an absolute choice to find out the choices ranking using similarity measures. Two types of standards have been used for evaluation, such as benefit standard (i.e., improving data analysis accuracy rate) and cost standard (i.e., reducing the data analysis processing time). Based on the benefit standard, the absolute choice is mathematically stated as given below.

$$c' = \left\{ \begin{matrix} \mathrm{MAX}\left(\mu_{c_i}(s_j)\right), \mathrm{MAX}\left(T(s_j, \mu_{c_i})\right), \\ \mathrm{MIN}\left(I(s_j, \mu_{c_i})\right), \mathrm{MIN}\left(F(s_j, \mu_{c_i})\right) \end{matrix} \right\} \quad (14)$$

Similarly, based on the cost standard, the absolute choice is mathematically represented as given below.

$$c' = \left\{ \begin{matrix} \mathrm{MIN}\left(\mu_{c_i}(s_j)\right), \mathrm{MIN}\left(T(s_j, \mu_{c_i})\right), \\ \mathrm{MIN}\left(I(s_j, \mu_{c_i})\right), \mathrm{MIN}\left(F(s_j, \mu_{c_i})\right) \end{matrix} \right\} \quad (15)$$

The Shapiro–Wilk test is applied in case of a null hypothesis (i.e., when the above two probabilities are the same), that the samples of patients '$p' = p'_1, p'_2, \ldots, p'_n$' is mathematically stated as given below.

$$ID = SWT = Round\left[\frac{\left(\sum_{i=1}^{n} c_i p_{(i)}\right)^2}{\sum_{i=1}^{n} (p_i - p')^2}\right] \quad (16)$$

From (16), '$p_{(i)}$' denotes the 'i – th order statistic' with sample mean of the patients represented by 'p'' respectively. From the above resultant values, choices are ranked accordingly, therefore forming a means for medical data analysis. The pseudo-code representation of Shapiro Wilk Neutrosophic Fuzzy is given below.

As given in the above Shapiro Wilk Neutrosophic Fuzzy algorithm, the objective remains in improving the data analysis accuracy with minimum processing time so that prompt and early decision-making are ensured. With this objective, first, neuro membership value is evaluated for the processed data. Second, two distinct operations, i.e., union and intersection are performed separately for three different forms, i.e., true, indeterminacy, and false representations. Third, to improve the benefit (i.e., data analysis accuracy) and reduce the cost (i.e., data analysis processing time), set of choices and standards are measured. Finally, the ideal alternative (i.e., signals) is computed. Then, the similarity measures between the ideal alternative (i.e., ideal accelerating signal)

Algorithm 2 Shapiro Wilk Neutrosophic Fuzzy

Input: Dataset 'DS', vital signs ('$V = V_1, V_2, \ldots, V_m$'), patients '$P = (P_1, P_2, \ldots, P_n)$'

Output: Robust remote healthcare data analysis

```
Initialize 'n'
Begin
For each Dataset 'DS' from patients 'P' recorded with vital signs 'V' and preprocessed resultant data (R)
Formulate neuro membership value as in equation (9)
Formulate fuzzy set as in equation (10)
For each patients 'P_i' and 'P_j'
Evaluate union and intersection operations as in equations (11) and (12)
Formulate features of choices corresponding to standards as given in equation (13)
Evaluate absolute choice with respect to benefit standard as given in equation (14)
Evaluate absolute choice with respect to cost standard as given in equation (15)
Evaluate Shapiro–Wilk test is applied in case of null hypothesis as in equation (16)
If 'ID = 1'
Then 'Data analyzed is baseline'
End if
If 'ID = 2'
Then 'Data analyzed is stress'
End if
If 'ID = 3'
Then 'Data analyzed is amusement'
End if
If 'ID = 4'
Then 'Data analyzed is meditation'
End if
End for
End for
End
```

and individual alternatives (i.e., individual accelerating signals) are obtained. Based on the derived results, the final data arrived at selected for data analysis (i.e., in the decision-making process) by employing, Shapiro–Wilk test. This novel Blinder Oaxaca Linear Regression-based Preprocessing and Shapiro Wilk Neutrosophic Fuzzy algorithm helps in not only ensure remote healthcare analysis but also in predicting the future health risk to a greater extent.

IV. EXPERIMENTAL SETUP

The proposed BO-SWNF data analytics for remote healthcare is explored and tested with other significant methods, namely Neutrosophic Multiple-Criteria Decision-Making (Neutrosophic MCDM) [1] and Grubbs's test under Neutrosophic Statistic (Grubb's test under NS) [2]. A persuading characteristic of the assessment metric is its potential to differentiate between results of different data analysis methods developed in Python using the WESAD dataset [23]. The efficiency of the data analysis method is evaluated by estimating the method's numerous execution measures or by monitoring the performance by several evaluation metrics. For the proposed work the method is validated in terms of:

- Energy consumption
- Data analysis accuracy
- Data analysis time

TABLE 4. Comparison of sample vs energy consumption.

Samples	Energy consumption (J)		
	BO-SWNF	Neutrosophic MCDM	Grubb's test under NS
150	225	255	285
300	240	280	325
450	295	315	380
600	305	345	435
750	325	375	515
900	340	435	625
1050	355	475	735
1200	370	515	780
1350	485	585	835
1500	525	635	900

A. PERFORMANCE ANALYSIS OF ENERGY CONSUMPTION

The first and foremost parameter of analysis for IoT sensor communication is the energy consumed during remote healthcare analysis. This is owing to the reason that while sensing the IoT sensors or device's data certain amount of energy is said to be consumed and hence has to be analyzed while communicating between IoT sensors also. The energy consumption is mathematically stated as given below.

$$EC = \sum_{i=1}^{n} Samples_i * EC\,(PRD) \tag{17}$$

From (17), energy consumption 'EC' is measured based on the samples (i.e., IoT sensors) involved in the process of communication '$Samples_i$' and the energy consumed while performing the preprocessing process or obtaining processed data '$EC\,(PRD)$'. It is measured in terms of joules (J). Table 4 given below lists the simulation results of energy consumption using the three methods, BO-SWNF, Neutrosophic MCDM [1] and Grubb's test under NS [2] respectively.

Figure 4 given above shows the energy consumption or the energy consumed while IoT sensor communication between patients is done for remote healthcare data. From the above figure, the energy consumption is found to be directly proportional to the number of samples of inputs acquired from two distinct devices separately from chest-worn and wrist-worn devices. In other words, increasing the number of samples of inputs acquired from patients causes an increase in the number and frequency of data to be analyzed. This in turn causes an increase in energy consumption and vice versa. However, simulations performed with 500 samples saw 225J of energy consumption using BO-SWNF, 255J of energy consumption using [1], and 285J of energy consumption

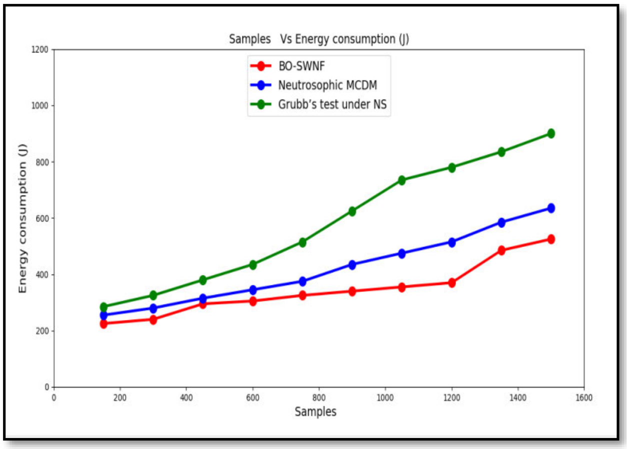

FIGURE 4. Average energy consumption of different sample of patients.

TABLE 5. Comparison of sample vs data analysis accuracy rate.

Samples	Data analysis accuracy rate (%)		
	BO-SWNF	Neutrosophic MCDM	Grubb's test under NS
150	88	83.33	78.66
300	86.35	82.15	77.25
450	85.15	83.35	76.55
600	84	83	76.35
750	84.35	83.15	77
900	84.85	83.45	77.55
1050	83.25	80	76.35
1200	82.15	77.35	76
1350	80	78	75.35
1500	81.35	79.35	76

using [2] respectively. The energy consumed during the preprocessing for data analysis using the BO-SWNF method was found to be comparatively lesser than [1] and [2]. The reason behind the improvement was due to the application of the Blinder Oaxaca Linear Regression-based Preprocessing algorithm. By applying this algorithm, two distinct vectors were produced for obtaining distinct types of data from two different devices with numerous vital signs. Also, with the aid of the data normalization process performed by utilizing the Blinder Oaxaca function wherein, MinMax Scaling has been applied separately to two different devices with numerous vital signs. As scaling functions are performed separately for two distinct devices, only when requested for preprocessing with the specified devices act on the processing. This in turn minimizes the energy consumed using BO-SWNF by 17 % compared to [1] and 37 % compared to [2] respectively.

B. PERFORMANCE ANALYSIS OF DATA ANALYSIS ACCURACY

The second factor of importance for analyzing data in remote healthcare data analytics is the data analysis accuracy rate. This is because of the reason that with the aid of this

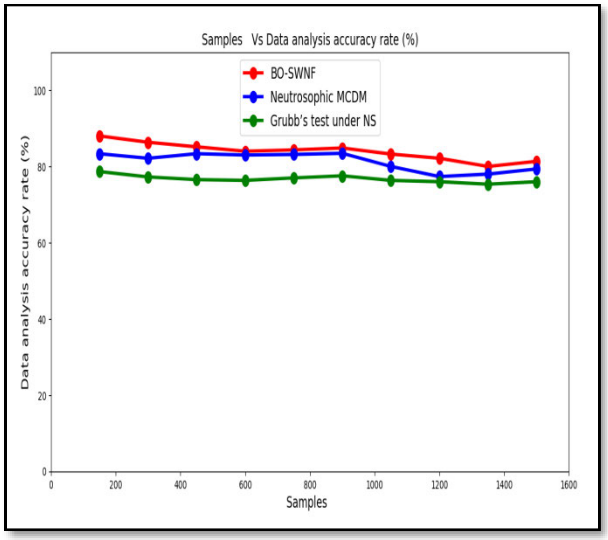

FIGURE 5. Average data analysis accurate rate of different sample of patients.

parameter significance of the proposed method implemented for IoT sensor communication in remote healthcare can be analyzed. The data analysis accuracy rate is mathematically stated as given below.

$$DA_{acc} = \frac{Samples_{CA}}{n} \tag{18}$$

From (18), the data analysis accuracy rate 'DA_{acc}' is measured based on the sample data correctly analyzed '$Samples_{CA}$' and the total observations involved for simulation 'n'. It is measured in terms of percentage (%). Table 5 given below provides the simulation results obtained from equation (18) for energy consumption using the three methods, BO-SWNF, Neutrosophic MCDM [1] and Grubb's test under NS [2] respectively.

Figure 5 given below shows the graphical representation of the data analysis accuracy rate with respect to 1500 different samples. The data analysis accuracy rate metric is considered as most critical, especially for data analysis scenarios as far as remote medical healthcare data is concerned. The below mentioned metric is evaluated in terms of percentage.

It shows that the data sample correctly analyzed during the IoT sensor communication task majorly contributes to average data analysis accuracy. From a performance point of view, higher values of all above-mentioned data analysis accuracy are preferred for better service provisioning and on the contrary, lower accuracy makespan may degrade overall performance. The data analysis accuracy rate was found to be comparatively higher using BO-SWNF than [1] and [2]. The reason behind the improvement was owing to the application of the MinMaxScaling function for resultant linear regressive decomposition of two distinct vectors i.e., chest-worn vector and wrist-worn vector respectively. Also, with the MinMaxScaling function resultant value, neutrosophic fuzzification was performed. With this fuzzification, sample data involved in analyzing correctly were found to be increased.

TABLE 6. Comparison of sample vs data analysis time.

Samples	Data analysis time (ms)		
	BO-SWNF	Neutrosophic MCDM	Grubb's test under NS
150	75	105	120
300	85	125.35	135.35
450	100.35	140.25	165.45
600	125.15	155.65	190.35
750	140.35	180.35	215.35
900	165.85	225.25	285.15
1050	210.25	240.35	305.35
1200	235.55	285.25	345.55
1350	250.35	305.25	360.35
1500	285.15	335.15	380.15

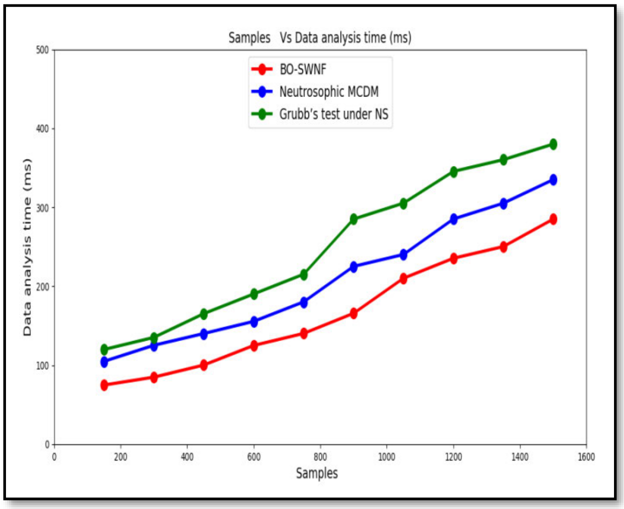

FIGURE 6. Average data analysis time of different sample of patients.

This in turn improved the data analysis accuracy rate using BO-SWNF by 3 % compared to [1] and 9 % compared to [2] respectively.

C. PERFORMANCE ANALYSIS OF DATA ANALYSIS TIME

Finally, the time involved in data analysis is measured. This is estimated as given below.

$$DA_{time} = n * Time\,[SWT] \tag{19}$$

From (19), the data analysis time 'DA_{time}' is measured based on the samples of patients involved in the simulation process between for remote healthcare data 'n' and the time consumed in testing for analyzing data 'Time [SWT]'. It is measured in terms of milliseconds (ms). Finally, table 6 given below lists the simulation results obtained from equation (19) for data analysis time from, BO-SWNF, Neutrosophic MCDM [1] and Grubb's test under NS [2] respectively.

Finally, figure 6 given above illustrates the data analysis time with respect to 1500 distinct sample data. From the above figure, the x-axis represents the number of samples involved in the data analysis process and the y-axis represents the average data analysis time performed for ten different simulation runs measured in terms of milliseconds (ms). Also from the above figure, it is inferred that increasing the number of sample data results in an increase in the number of patients' data. In all three methods, increasing the number of sample data results in an increase in data analysis time also. However, a significant improvement is observed using the BO-SWNF method. This is because of the application of the Shapiro Wilk Neutrosophic Fuzzy algorithm. By applying this algorithm, with the processed data, neuro membership value was formulated. With the formulated neuro membership value, two distinct operations, namely, union and intersection were performed separately for three different types of representations, i.e., true, indeterminacy, and false representations. Followed by this, similarity measures between ideal accelerating signals and individual accelerating signals were measured. Finally, the decision-making using Shapiro–Wilk test was performed. With this test, the data deviation from a normal distribution is said to be identified that in turn assists in reducing the data analysis time using the BO-SWNF method by 22 % compared to [1] and 34 % compared to [2].

V. CONCLUSION

Data analysis examines raw datasets to identify the trends, arrive at conclusions, and acquire the probabilities for enhancement. The exiting Neutrosophic MCDM was utilized to prioritize the group to assign the COVID-19 vaccine. However, the classification accuracy and the energy of the decision-making process were not considered. The traditional Grubbs's test under CS was employed to discover each observation in the medical data. But, it failed to estimate the accuracy and time. In this paper, the remote healthcare analysis employs both the present and the historical data to gain insight into the decision-making process. Moreover, neutrosophic fuzzy sets have made an appearance as a new technique that aids in decision-making to ensure accurate and timely data analysis. In this paper, we proposed a BO-SWNF data analytics for remote healthcare. The proposed advantages of the BO-SWNF method are used for the decision-making process to handle the robustness and accuracy of remote healthcare data analytics with minimum time. The reason for accurate, timely data analysis and ensuring early decision-making is applied to Blinder Oaxaca Linear Regression-based Preprocessing algorithm and Shapiro Wilk Neutrosophic Fuzzy algorithm. The proposed BO-SWNF method gives higher values for data analytics accuracy, and the lowest values for energy consumption, and data analytics time when compared with the existing Neutrosophic MCDM [1] and Grubb's test under NS [2]. The results obtained from the work indicated the significance of preprocessing and data analysis and hence assisting critically ill individuals, health workers, and elderly patients. Simulation results revealed that the proposed BO-SWNF method outperforms Neutrosophic MCDM [1] and Grubb's test under NS, in terms of energy consumption by 54 %, data analysis accuracy rate by 12 %, and data analysis time by 56 % respectively. Though significant measures were taken in analyzing the energy consumption, accuracy and time, security factors involved in data analysis were not focused.

In the future performance of the proposed method will be further enhanced by employing some blockchain-based methods in modeling the fuzzy towards ensuring safe and secured data analysis. We will focus on a blockchain based secured method incorporated with a fuzzy mechanism to increase the scalability and minimize the complexity towards increased security of the system.

CONFLICT OF INTERESTS

There are no conflicts of interest for all authors.

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OSAMAH IBRAHIM KHALAF received the B.Sc. degree in software engineering from Al-Rafidain University College, Iraq, the M.Sc. degree in computer engineering from Belarussian National Technical University, and the Ph.D. degree in computer networks from the Faculty of Computer Systems and Software Engineering, University Malaysia Pahang. He is currently a Senior Engineering and Telecommunications Lecturer with Al-Nahrain University. He has 17 years of university-level teaching experience in computer science and network technology and has a strong CV about research activities in computer science and information technology projects. He has overseas work experiences in universities, such as Binary University, Malaysia, and University Malaysia Pahang. He has published many articles that are indexed in ISI/Thomson Reuters and has also participated and presented at numerous international conferences. He holds a patent and has received several medals and awards due to his innovative work and research activities. He has good skills in software engineering, including experience with.Net, SQL development, database management, mobile applications design, mobile techniques, Java development, Android development, and IOS mobile development, cloud systems and computations, and website designs. He is the Editor-in-Chief and a main guest editor in many Scopus and SCI index journals. .

RAJESH NATARAJAN received the B.Sc. degree in computer science from Madras University, the master's degree in computer application from Thiruvalluvar University, and the Ph.D. degree in computer science from Bharathiar University. He is currently working as a Lecturer with the University of Technology and Applied Sciences, Shinas, Oman. He has presented articles in national and international conferences and also published articles in reputed indexed journals like SCI, WoS, and SCOPUS. His research interests include data mining, machine learning, big data analytics, blockchain technology, and data privacy and security.

NATESH MAHADEV received the B.E. degree in computer science engineering and the M.Tech. and Ph.D. degrees in computer science and engineering from Visveswaraya Technological University (VTU). He is currently working as an Associate Professor with the Department of Computer Science and Engineering, Vidyavardhaka College of Engineering, Mysuru, Karnataka, India. He has published various articles in reputed national and international journals. His research interests include digital image processing, blockchain, machine learning, artificial intelligence, and data science.

PRASANNA RANJITH CHRISTODOSS received the bachelor's, M.Sc., M.Phil., and Ph.D. degrees in computer science from Bharathidasan University, Trichy, India, in 1995, 1997, 2004, and 2017, respectively. He has more than 23 years of teaching experience at different colleges and universities in India, Libya, and Oman. He is currently a Faculty and a Research Chair with the Department of Information Technology, University of Technology and Applied Sciences, Shinas, Oman, since October 2011. He has organized various workshops, seminars, and symposiums toward professional research and development. He has published many research articles in international journals and conferences of high repute. He has ample experience in the field of web designing having widespread familiarity in ASP.Net (C#) and MS SQL Server. His research interests include machine learning, deep learning, nature-inspired algorithms, soft computing, parallel algorithms, genetic algorithms, and *ad hoc* networks. He was awarded as the Best Faculty for three consecutive years.

THANGARASU NAINAN received the Ph.D. degree in computer science. He is currently working as an Assistant Professor with the Department of Computer Science, Karpagam Academy of Higher Education, Coimbatore. His research interests include cluster computing, cryptography and network security, cloud computing, intelligent systems, and information security in large database and data mining.

CARLOS ANDRÉS TAVERA ROMERO (Member, IEEE) is currently working as a Engineering Faculty Member, and also with the COMBA Research and Development Laboratory, Universidad Santiago de Cali, Colombia. He has published articles in reputed indexed journals like SCI, WoS, and SCOPUS.

GHAIDA MUTTASHAR ABDULSAHIB is currently working as a Faculty with Computer Engineering Department, University of Technology, Iraq. She also published articles in reputed indexed journals like SCI, WoS, and SCOPUS. Her research interests include networks and communication. She received a lot of awards in computer engineering.